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Multi-criteria robust optimization framework for bridge adaptation under climate change

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ABSTRACT

In order to adapt civil infrastructure to changing climate conditions, quantifiable and deep uncertainties must be integrated into the decision-making process. The quantifiable uncertainties, i.e. variability for which a likelihood can be defined, are typically integrated into the management process by considering the reliability or risk level of a structure. The deep uncertainties, i.e. the variability for which a likelihood cannot be defined, are beginning to be integrated in the decision making process as a few robust decision making procedures have been proposed. However, the deep uncertainty associated with the multiple feasible future climate scenarios also provokes a "wait and see" mentality for some decision makers, causing the flexibility of a strategy to be valued. This paper introduces the Gain-Loss Ratio (GLR) as a metric that systematically quantifies what may be gained by postponing adaptation while also considering what is lost with the delay. Additionally, bi-objective optimization models for optimizing bridge adaptation strategies under deep uncertainties are proposed; the advantages and disadvantages of each are highlighted as they pertain to the management of a typical riverine bridge. Two rivers are considered that have comparable climate change trends as those predicted for the Columbia and Mississippi Rivers. It is demonstrated that the desire for flexibility may be justified for certain locations, but may be detrimental in others.

1. Introduction

The uncertainties of climatechange increase the difficulties facing decision makers when it comes to determining optimal adaptation strategies for civil infrastructure[1–3]. The challenges lie in the efficient integration of both quantifiable and deep uncertainties while also accommodating the risk attitudes and skepticism of individuals within the decision making group. The field of adaptation engineering focuses on ensuring that current and new assets are protected from both near- and long-term changes in climate conditions [4,5]. It is an active field of research, with substantial emphasis on managing civil infrastructure [6–8]. This paper proposes a methodology that balances the benefit of adapting bridges with the flexibility of a strategy. Additionally, both the quantifiable and deep uncertainties associated with the climate change are systematically integrated into optimization formulation.

Quantifiable uncertainties are those for which a probability of occurrence is well defined; whereas deep uncertainty refers to instances where probabilities cannot be agreed upon [4,9]. Examples of quantifiable uncertainties may include those associated with the physical properties of a structural system, the natural variability of wind, precipitation, and flooding, and the variability in structural deterioration processes. The presence of these uncertainties typically precipitate the use of vulnerability assessment methodologies to evaluate the effectiveness of adaptation strategy. The probability of failure, reliability, or risk have been integrated in optimization routines in order to determine optimal strategies [10–14].

Deep uncertainties, those for which probabilities cannot be defined, may include future economic and/or climate scenarios [15,4]. In the climate adaptation engineering, deep uncertainties stem from both the Representative Concentration Pathways (RCPs) used to define greenhouse gas trajectories and the Global Climate Models (GCMs) to predict future climate scenarios. Since no likelihood can be assigned to the different RCPs [5] and there is no consensus on which GCM is the most applicable [16], there is no probability that can be objectively assigned to the occurrence of future climate scenarios. This represents a unique challenge to decision makers who must either aggregate the future climate scenarios into one or otherwise account for all potential scenarios in the decision-making process.

The deep uncertainties of climate change pose two unique problems. First, the scenario uncertainty drives a desire for flexibility, as well as efficiency, in an adaptation strategy. Second, decision makers must aggregate the future climate scenarios into one, or otherwise account

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for all potential scenarios in the decision-making process.

Typically, the efficiency of an adaptation strategy is quantified by the benefit, Benefit-Cost ratio (BCR) or Net Present Value (NPV), all of which have been integrated into the development of management strategies [11,19]. The benefit of an adaption strategy represents the reductions in risk achieved by that strategy. BCR and NPV consider both the benefit for society, and the economic efficiency of the action. However, some decision makers may also prefer to consider the option value in a strategy (i.e. the value of the flexibility of the strategy). This is related to the timing of adaptation: postponing adaptation may allow the decision maker to observe climate conditions and wait for improved climate information to become available. This then allows the flexibility of adapting at a more favorable time or not adapting. While the desire for flexibility in adaptation strategies has been identified and discussed qualitatively [4,20,21], there is no systematic methodology for assessing the flexibility of an adaptation strategy as it pertains to the management of structural assets.

When decision makers have identified the metric with which to evaluate an adaptation strategy, they must still determine how they are going to aggregate the performance across all scenarios. Robust optimization models have been developed to find optimal strategies against potential scenarios without requiring the probabilities of occurrence of scenarios to be known. Non-probabilistic robust optimization models, such as maximin or maximax models, consider the performance of the adaptation strategy against all scenarios without assigning a probability of occurrence to them [17]. Maximin formulations typically optimize over the worst-case scenario, while maximax formulations typically optimize over the best possible scenario. By choosing the formulation of the problem, the decision makers are predisposing themselves to a particular preference: maximin and maximax formulations assume a pessimistic and optimistic outlook on future scenarios, respectively. Alternatively, a robustness index can be used to assess the variability of the performance of a strategy across all potential scenarios [9]; thus, aggregating the response across all scenarios and enabling the use of a maximization optimization formulation. When optimizing using the robustness index, the decision makers are not giving preference to any one scenario, but consider how well the strategy performs across all scenarios. It implicitly assigns the same probability of occurrence to all scenarios. Thus, this last model falls into the category of a probabilistic robust optimization model, i.e. a stochastic optimization model.

This paper proposes a Gain-Loss Ratio (GLR) to account for the potential gains and the potential losses associated with the delay. This metric systematically assesses the value in delaying adaptation in order to achieve a flexible strategy. Furthermore, this paper proposes bi-objective robust optimization models that simultaneously optimize the conflicting objectives of efficiency (as defined with the BCR) and the flexibility (as defined with the GLR). The methodology is applied to two illustrative examples; both include a typical bridge over a river vulnerable to climate changes. The climate change trends in the two examples are modeled after expected trends in the Mississippi and Columbia Rivers in the United States in order to identify the effect of spatial variation of the climate change hazard.

2. Climate change

Natural and anthropogenic factors have forced an overall change in the climate. Sea level rise, increasingly intense precipitation, and increasingly intense hurricanes are among the major components of climate change that affect riverine bridges [1,21]. Heat waves, arctic warming, and increased temperature and humidity may also affect the life-cycle performance of civil infrastructure [1,22,23]. Together, all of these aspects define the climate change hazard and may have adverse effects on the performance of civil infrastructure [5,22]. This paper will focus on the changes in flooding that accompany the climate change hazard. Alternative aspects of the climate change hazard may also be included, but since hydraulic events (including scour, debris impact,

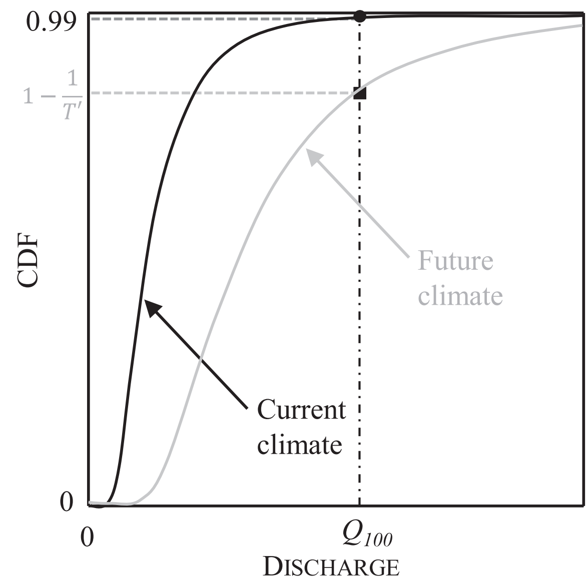

Fig. 1. The cumulative distribution of discharge for a current and future climate.

debris accumulation, among others) are the predominant source of damage to bridges [24], river discharge and flooding are the main hazards considered herein. It is important to note, however, that the framework and concepts presented in this paper for the development of optimal adaptation strategies for riverine bridges can be applied to other aspects of climate change for other civil infrastructure systems.

The change in flooding is typically described by a change in the return period of a discharge of a specific magnitude; typically, this is the discharge associated with the 100-year flood [25–27]. The 100-year flood discharge under the current climate, denoted herein as Q_{100}, is associated with a probability of exceedance of 0.01, as shown in Fig. 1. A statistical analysis of outputs from GCMs at the end of a period of time provides the probability of exceedance of the Q_{100} discharge for a future climate. The climate change is then reported as a change in the recurrence interval of the 100-year flood; in Fig. 1 the future recurrence period is denoted as *T'*.

The predicted climate change effect on flooding varies for different RCPs and different GCMs. Thus, a set of future recurrence intervals exists for a specific location rather than a single value. Since no likelihoods can be assigned to the different RCPs [5] and no agreement (at this time) can be made on which GCM is most accurate [16], no likelihood can be assigned to the set of future recurrence intervals; the scenario uncertainty and model uncertainty are both sources of deep uncertainty.

Hirabayashi et al. [27] provided insight into the changes into the spatial variation of global flooding. The outputs from 11 GCMs for RCP 8.5 were used to obtain a change in the return period of the 100-year flood for various rivers across the world. The minimum, 25th percentile, median, 75th percentile, and maximum return periods from the 11 outputs were reported for rivers across all continents. Two rivers in the United States were reported: the Mississippi and the Columbia. The expected climate trends in these rivers are detailed in Fig. 2.

The predicted shifts in the return periods for these two rivers highlight two main points: (1) the variation in GCMs is significant and may be contradictory. For the Columbia River, 8 out of 11 models determined that the return period would decrease, leaving 3 models suggesting that the return period would increase [27]. This can also be interpreted as 8 models indicate an increase in Q_{100}, while 3 indicate a decrease. For the Mississippi River, 7 out of 11 models determined that the return period would increase, leaving 4 models suggesting that the return period would decrease. (2) It is essential to consider the spatial

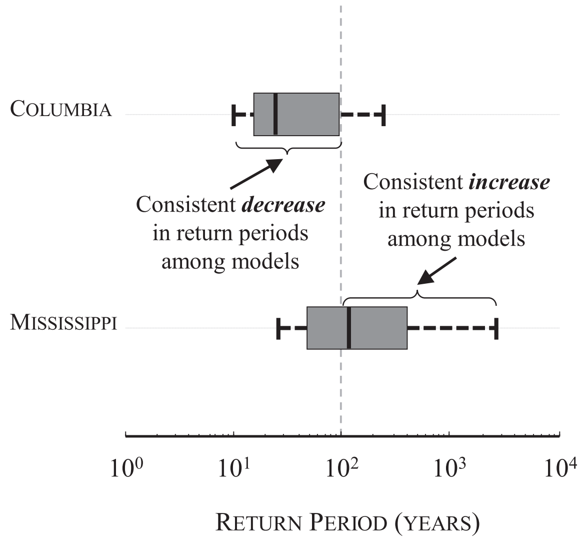

Fig. 2. Box and whisker plots for the projected return periods of the 100-year flood for the Columbia and Mississippi river at the end of the 21st century (adopted from Hirabayashi et al. [27]). The interquartile range (25th-75th percentile) is indicated by the height of the grey box, the solid line within each box indicates the median, and the dashed lines represent the maximum and minimum return periods.

effects of climate change when developing adaptation plans for structures: while flooding in Columbia River is consistently projected to increase in severity, the severity of flooding for the Mississippi river is consistently projected to decrease.

3. Evaluation of adaptation strategies

An adaptation strategy is a plan to mitigate the adverse impacts of climate change. Adaptation strategies include the type of adaptation action, a_a, and the time the adaptation action is applied to the structure t_a. Strategies are optimized with respect to a planning horizon, T_{ph}, since it is essential to define the length of time into the future that must be accounted for. In the life-cycle analysis of structures, this may also be referred to as the expected life of the structure, service life, or expected remaining life.

In order to determine an optimal adaptation strategy, decision makers must first choose a performance metric with which to evaluate the life-cycle implications of a strategy. Recently, an emphasis on structural performance and the consequences of failure of a structure has led to the continued use of the risk metric. Alternatively, the benefit-cost ratio assesses both the structural performance and the consequences of failure and the cost of the action and has been used as the grounds for decision making. However, if there is a desire to wait for more accurate information regarding future scenarios, the flexibility of an adaptation strategy may also be important to consider.

4. Structural performance and risk

In order to evaluate the effectiveness of an adaptation strategy, the time-variant risk profile must be estimated. The performance of a structure may decrease over time as individual components corrode and the capacity of the structure deteriorates, or, as the intensity of natural hazards increase the demand on the structure. Though, in some regions, changes in climate may also decrease the demand on the structure. In either likelihood, the time-variant performance of a structure must be assessed in order to determine what adaptation actions should be taken. The probability of failure of a structure is defined as

$$P_f(t) = P[S(t) < D(t)] \tag{1}$$

where $S(t)$ is the time-variant capacity of the structure and $D(t)$ is the time variant demand. By defining performance probabilistically, the quantifiable uncertainties are integrated into the assessment methodology.

Risk incorporates the impact that a structural failure has on the community it serves. The consequences of failure, $\kappa(t)$, modify the structural performance to formulate the risk

$$R_m(t) = P_{f,m}(t)\kappa(t) \tag{2}$$

where $R_m(t)$ is the time-variant risk associated with adaptation strategy m, $P_{f,m}$ (t) is the time-variant probability of failure for adaptation strategy m. The adaptation strategy is composed of a specific adaptation action a_a and adaptation time t_a. A qualitative representation of the time-variant profile of annual risk for an adaptation strategy m, where an adaptation action is applied at time t_a is shown in Fig. 3a. The increase in annual risk over time may be attributed to climate change-

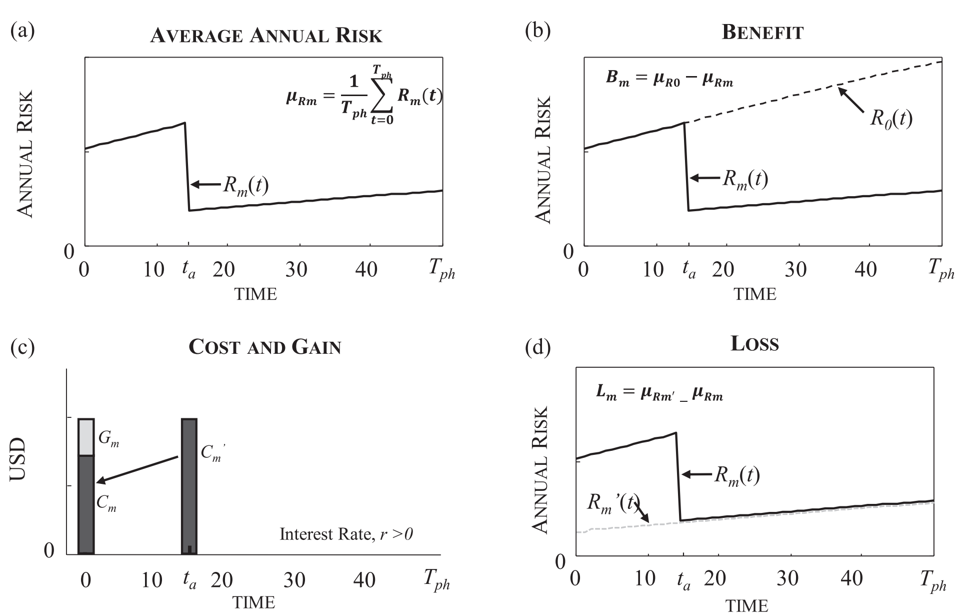

Fig. 3. Conceptual depiction of the time-variant risk profiles and cost information needed to determine the (a) average annual risk, (b) benefit, (c) cost and gain, and (d) loss for adaptation strategy m.

related increases to the hazard, structural deterioration, or a combination of both. The sharp decrease in annual risk at t_a is due to the increase in structural capacity provided by the adaptation action. The average annual risk μ_{Rm}, or the mean value of the annual risk over the planning horizon of the management strategy *m,* is

$$\mu_{Rm} = \frac{1}{T_{ph}} \sum_{t=1}^{T_{ph}} R_m(t) \tag{3}$$

provides a single metric to quantify the life-cycle risk associated with the adaptation strategy. In life cycle performance assessment, the maximum annual risk, i.e. the largest annual risk over the required planning horizon, or cumulative risk, i.e. the summation of risk over the planning horizon, has also been used to evaluate management strategies [13,28]. However, average annual risk is considered in this paper since it has a unique value for all potential strategies and capture the reduction in risk due to the effectiveness of adaptation actions.

5. Decision support for adaptation: Metrics

In order to determine an optimal adaptation strategy, decision makers must first choose a performance metric with which to evaluate the life-cycle implications of a strategy. Typically, the metric is utility, benefit, or BCR. Modern economic theory then states that the optimal solution maximizes the metric. However, the presence of multiple feasible future scenarios also instills the desire for flexibility in adaptation strategies. Thus, a single metric fails to capture the complexities in the decision. The following section provides a review of the BCR and how it is formulated and introduces the GLR as a metric to systematically address the desire for strategies to be flexible.

5.1. Benefit-Cost ratio

Due to the vast amount of bridges needing maintenance and repair [29] and the limited availability of financial resources, the economic effectiveness of an adaptation strategy is often included in the decision-making process. The benefit discussed in the previous section, comes at a cost to the managers; which, for publicly funded projects, becomes a burden on the taxpayers. Therefore, benefit-cost analysis is used to systematically determine options that are economically efficient, as well as beneficial. The benefit-cost analysis, also referred to as cost-benefit analysis, is a systematic method used to evaluate the performance of alternative options. The benefit-cost ratio BCR normalizes the benefit (i.e. the reduction in life-cycle risk) to the life-cycle cost. This ratio not only provides a way to prioritize management strategies but also helps in identifying which ones are profitable (i.e. have a benefit higher than the cost, BCR > 1).

The benefit of an adaptation strategy is the improvement achieved by the adaptation action applied at the associated time. Benefit is, herein, defined as the reduction in average annual risk an adaptation strategy provides when compared to the average annual risk of the unmaintained structure

$$B_m = \mu_{R0} - \mu_{Rm} \tag{4}$$

where μ_{R0} is the average annual risk of the unmaintained structure, and B_m is the benefit associated with adaptation strategy *m*. Thus, in order to calculate the benefit for a strategy, a life-cycle risk assessment must be performed for both the unmaintained structure in order to determine $R_0(t)$ and for the structure considering adaptation strategy *m* in order to define $R_m(t)$ as shown in Fig. 3b. It is important to note that benefit derived from an adaptation strategy is dependent on the future climate scenario. Thus, adaptation strategy *m* will have a different benefit for each climate scenario *k* and is denoted as B_{mk}.

The benefit cost ratio *BCR* for an adaptation strategy *m* is defined as

$$BCR_m = \frac{B_m}{C_m} \tag{5}$$

where C_m is the present value of the cost of the adaptation action. It is assumed that the cost of each maintenance action is constant over the planning horizon: the cost of implementing adaptation strategy *m* at the time that the adaptation action is applied is denoted as C'_m. The cost is converted to constant value in order to compare the BCRs of strategies where actions are performed at different times. In this analysis, the present value is used as the basis of comparison, and the cost associated with an adaptation strategy must be discounted to the present value

$$C_m = \frac{C'_m}{(1+r)^{t_a}} \tag{6}$$

where t_a is the year that the retrofit action is applied in adaptation strategy *m*, and *r* is the discount rate. Likewise, the present value of consequences are used when evaluating risk in Eq. (2), and is thus implicit in the benefit formulation. Profitable strategies will have a return on investment that is larger than the investment cost (i.e. BCR > 1). Strategies with larger BCRs are preferred as they have a larger benefit per dollar invested. Similar to benefit, the benefit-cost ratio for an adaptation strategy is dependent on the future climate scenario that is included. Thus, each adaptation strategy *m* will have a benefit-cost ratio for each climate scenario *k*, BCR_{mk}.

5.2. Gain-Loss ratio

While the main goal of adaptation engineering is to ensure that existing and new infrastructure are protected from the long-term effects of climate change [5], another goal may be to keep the consequences of being wrong about the future climate as low as possible [2,7,20]. This promotes the desire for a flexible strategy (i.e. one that postpones adaptation to allow the decision maker to observe market conditions and wait until a more favorable time to act or to observe climate information and abandon (or otherwise revise) the strategy). For example, in an urban planning problem the consequences of underestimating future flooding may mean that early investments in development are made and then lost due to permanent inundation or extreme flooding. The decision to develop early is an inflexible strategy, that may seem viable since there is the prospect of short term profit, but is infeasible due to long-term losses. Alternatively, not developing an area is a flexible strategy. The decision makers wait for further climate information to become available before acting, and may develop or not develop based on the updated information. However, it comes at the cost of missing the early gains that could be realized if a favorable climate change were to occur.

The concept of flexible options can be extended to structural management: an adaptation strategy that defers application of retrofit actions until further information is available may be defined as flexible since it allows the decision maker to “wait and see” what to do once more information becomes available. This allows the decision maker the opportunity to not spend money on retrofits if it turns out that the impact of climate change is favorable. However, if climate change is unfavorable, the delay in action comes at the cost of losing out on potential reductions in risk. The following formulations for gains, losses, and GLR are presented as a systematic methodology for assessing the impact of delaying adaptation.

Gain is herein defined as the present value of interest earned by delaying investment. It considers the timing of the application of retrofit. The additional time before the application of adaptation measures also may lead to advancements in technology that reduce the uncertainty associated with future scenario prediction and/or observational information can be used to update estimates. However, in order to provide a systematic methodology for quantifying the value of delaying the action, the value of these advancements and information are omitted. Instead, only the financial gains made by delaying are included. Considering only the direct economic gain, the gain term is defined as the difference between the present value of the cost of the retrofit option included in adaptation strategy *m* if it were applied at

time t_0 (i.e. C'_m) and the present value of the cost of the retrofit option included in adaptation strategy m applied at the time specified in adaptation strategy m (i.e. C_m)

$$G_m = C'_m - C_m \tag{7}$$

Conceptually, the costs and gains of adaptation strategy m are shown in Fig. 3c. C'_m is the dollar amount paid at the time of application t_a. The present value of this cost, C_m, is assessed with Eq. (6). The gain, as shown in Fig. 3c, for this strategy is difference between the present value of the cost of the adaptation action included in the adaptation strategy if it were applied at $t_a = 0$, and the present value of the action as applied at t_a for the adaptation strategy. This gain, however, comes with an opportunity loss. By foregoing early action, the maximum reduction in average annual risk would not be able to be achieved. Thus, the loss associated with delay is defined as

$$L_m = \mu'_{Rm} - \mu_{Rm} \tag{8}$$

Loss, like gains, considers only timing of the application of retrofit, and therefore compares the average annual risk of the retrofit option included in adaptation strategy m applied at the time specified for adaptation strategy m (i.e. μ_{Rm}) and the average annual risk of that same option if it were applied at time t_0 (i.e. μ'_{Rm}). This is shown conceptually in Fig. 3d.

Comparable to the economic efficiency, it is important to assess the flexibility in terms of both the benefit (i.e. gain, G) to cost (loss, L). Therefore, the gain-loss ratio for adaptation strategy m, GLR_m, is defined as

$$GLR_m = \frac{G_m}{L_m} \tag{9}$$

In this way, a strategy with high gains accrued by delaying adaptation and low potential losses would have a high GLR. Strategies with low gains but large losses would have a low GLR. The options with the highest GLR are preferred. It is important to note that GLR is not a direct value of flexibility, but, instead, a metric that systematically assesses the effect of delaying adaptation. The gain-loss ratio for an adaptation strategy m will vary for each climate scenario k, and will be denoted as GLR_{mk}.

6. Decision support for adaptation: Frameworks

The performance of an adaptation strategy is assessed for multiple climate change scenarios, and unless there is a systematic methodology for aggregating the performance across the set of scenarios, the search for an optimal strategy cannot proceed. Thus, robust optimization models and decision-making tools have been developed in order to integrate the uncertainties associated with climate change into adaptation planning [4,9,16,30,31]. There are two predominant formulations associated with the non-probabilistic, robust optimization models: maximin and maximax.

Maximin formulations inherently plan for the worst possible outcome while trying to maximize payoff. They are typically associated with a 'risk-averse' attitude and take the form

$$m^* = \max_{\Phi}(\min_{\Psi} Payoff_{mk}) \tag{10}$$

where m^* is the optimal adaptation strategy composed of the optimal adaptation action of $a_a{}^*$ and its time of application $t_a{}^*$, Φ is the set of potential adaptation strategies $m = 1, 2, \ldots, M,$ and Ψ is the set of climate scenarios $k = 1, 2, \ldots, K$. For the adaptation of civil infrastructure, $Payoff_{mk}$ can refer to the BCR_{mk} or GLR_{mk} of an adaptation strategy.

Maximax formulations involve maximizing the maximum payoff, inherently assuming an optimistic view on future scenarios, and are typically associated with a 'risk-taking' attitude. The maximax formulation takes the form

$$m^* = \max_{\Phi}(\max_{\Psi} Payoff_{mk}) \tag{11}$$

By formulating the adaptation problem in either a maximax or maximin approach, an optimal strategy can be systematically determined without knowing (or subjectively assigning) the probability of the future scenarios. However, there may be significant difficulties in integrating such formulations into the decision-making process if there are divergent risk-taking perspectives within a group of decision makers.

As an alternative, a robustness index has previously been proposed as

$$RI_m = \sqrt{\frac{1}{K}\sum_{k=1}^{K} Payoff_{mk}^2} \tag{12}$$

where RI_m is the robustness index for payoff for adaptation strategy m [9]. This can then be integrated into an optimization formulation to maximize robustness

$$m^* = \max_{\Phi}(RI_m) \tag{13}$$

in order to identify an adaptation strategy that performs well across all scenarios. While this methodology does not explicitly assign a probability to each scenario, the contribution of each scenario is equally weighted. Thus, it implicitly assigns an equal probability to the occurrence of all scenarios. Based on Eq. (12), the robustness index is always non-negative and therefore does not differentiate between positive and negative values of the payoff metrics. This may prove to be a significant impediment to the use of RI as metric if future climate and/or economic scenarios yield negative payoff values.

In order to apply the above formulations to climate change adaptation problem, the robust optimization models must be expanded to their bi-objective forms since a group of decision makers may want to simultaneously maximize the economic efficiency and the flexibility of their chosen adaptation strategy. The following is a description of the three bi-objective formulations included in this paper used to identify the optimal adaptation strategy: a pessimistic (maximin), optimistic (maximax), and robust approach.

6.1. Maximize Minimums: A pessimistic approach

The pessimistic formulation accounts for the worst-case scenario when making decisions. The non-probabilistic maximin model for the bi-objective problem does not assign any likelihood to climate scenarios and takes the form

$$\text{Objective:} \max_{\Phi}(\min_{\Psi} BCR_{mk}) \quad and \quad \max_{\Phi}(\min_{\Psi} GLR_{mk}) \tag{14}$$

$$\text{Find:} m^* \tag{15}$$

$$\text{Given:} \Phi, \mathscr{C}, S_A, \Psi, S_B \tag{16}$$

where m^* includes the adaptation action a^* and the time of adaptation $t_a{}^*$, Φ is the set of potential adaptation strategies, $\mathscr{C}$ is the set of costs for the potential adaptation actions in Φ, S_A is the structural design information for all potential adaptation actions, Ψ is the set of climate scenarios, and S_B is the structural design information for the bridge.

6.2. Maximize Maximums: An optimistic approach

The optimistic formulation assumes that the best of all possible scenarios will occur and that the optimal strategy should be developed around that. The bi-objective formulation of the optimistic approach takes the form:

$$\text{Objective:} \max_{\Phi}(\max_{\Psi} BCR_{mk}) \quad and \quad \max_{\Phi}(\max_{\Psi} GLR_{mk}) \tag{17}$$

$$\text{Find:} m^* \tag{18}$$

$$\text{Given}:\Phi,\mathscr{C},S_A,\Psi,S_B \tag{19}$$

In the single objective formulation, the maximax model relies on the assumption that the best possible scenario will occur. When extended to the bi-objective formulation with conflicting objectives, this assumption may be invalid since the best scenario for one metric may not be the best scenario for the other. Thus, the objective function values associated with the optimal solution found for this formulation may be an over estimate of what is actually feasible. This concept is further discussed in the illustrative example.

6.3. Maximize robustness indices

The final bi-objective formulation relies on an implicit assignment of probability to the occurrence of each climate change scenario included in the assessment. It is formulated as follows in order to find a strategy the performs well under most scenarios

$$\text{Objective}:\max_{\Phi}(RI_m^{BCR}) \quad and \quad \max_{\Phi}(RI_m^{GLR}) \tag{20}$$

$$\text{Find}:m^* \tag{21}$$

$$\text{Given}:\Phi,\mathscr{C},S_A,\Psi,S_B \tag{22}$$

7. Illustrative Example

An illustrative example is herein presented for the management of a riverine bridge under the climate change hazard of flooding. The illustrative example is divided into two sub-examples. The only difference between the examples is the climate change trends expected for the given river. Example A includes the riverine bridge over a river with potential climate change trends similar to those expected in the Columbia River. Example B includes the same riverine bridge over a river with potential climate change trends similar to the Mississippi river. This section details the rivers and their climate change trends for Examples A and B, then details the bridge structure and reviews the adaptation measures that may be applied to prevent failure.

The rivers included in Example A and B have a 100-year flood discharge assumed to be 310 m^3/sec, with the discharge following a Lognormal Type 3 distribution [32] with a mean of 88 m^3/sec and standard deviation of 60 ft^3/sec for the 20th Century climate. The change in discharge over time for River A, i.e. the river considered in Example A, follows that expected in the Columbia River. The climate change scenarios considered in the illustrative example address range of GCM outputs include the return periods corresponding to the minimum value, 25th percentile, median, 75th percentile, and maximum value for RCP 8.5 as presented in Hirabayashi et al. [26]. These are denoted as Climate Change Scenarios CCS_k where k is 1, 2, 3, 4, and 5, respectively, and make up the set of climate scenarios Ψ. CCS_0 is the current (20th Century) climate. Since the predominant source of uncertainty for precipitation predictions is model uncertainty [33], the inclusion of only these climate change scenarios is deemed sufficient for the illustrative examples. However, the methodology proposed in this paper is developed generically and can accommodate other RCPs and GCMs. The discharge distribution at the end of the 21st century for the five *CCSs* included on Example A are shown in Fig. 4a. The change in discharge distribution for River B, i.e. the river considered in Example B, follows that expected in the Mississippi River [27] the discharge distribution at the end of the 21st century for the five *CCSs* included are shown in Fig. 4b.

In order to assess the average annual risk for a potential adaptation strategy, it is assumed that there is a linear increase in the discharge over the 100-year span to achieve the change in probability of occurrence of the initial climate's 100-year discharge event. It should be noted, that this assumption may vary from both that predicted with the GCM and the actual future climate. While the illustrative example assumed the linear trend, the same methodology for adaptation optimization can be applied to any available time variant climate trend.

The structural design of the riverine bridge S_B included in both illustrative examples is detailed in Mondoro and Frangopol [18] along with the methodology for assessing the probability of failure and risk of the bridge for a given climate. In summary, the probability of deck failure, pier failure, and/or foundation failure is first calculated, the probability of failure is estimated, and the total risk for the bridge is assessed. This methodology is repeated at each point in time in order to determine the time-variant risk profile of a given adaptation strategy. For Examples A and B, the time variant risk profiles for the bridge under the future climate change scenarios are shown in Fig. 5 for a planning horizon, T_{ph}, of 60 years. The risk profiles correspond to an unmaintained structure. A discount rate of zero (i.e. $r = 0$) is assumed in order to highlight the direct impacts of future climate change scenarios. For Example A, the annual risks for CCS_1 through CCS_4 increase over time. Only CCS_5 corresponds to a decrease in annual risk that is attributed directly to anticipated changes in the climate. However, for River B, the majority of climate scenarios (i.e. CCS_3 through CCS_5) correspond to a decrease in annual risk as time progresses.

The design variables in the optimization routine include both the type and timing of adaptation. The adaptation action a_a may include the application of (1) riprap around the pier, (2) steel restrainers (3) shear keys, (4) riprap and steel restrainers, or (5) riprap and shear keys. The structural details S_A, cost $\mathscr{C}$, and methodology for assessing failure of each of these retrofit measures is detailed in Mondoro and Frangopol [18]. The time of adaptation t_a may be any integer ranging from year 1 to one year before the end of the planning horizon (i.e. $T_{ph} - 1$). The set composed of all possible combinations of adaptation actions and adaptation time form the set of potential adaptation strategies Φ. The optimization problem includes an assumed discount rate of 0.04 which is considered to remain constant over the planning horizon.

8. Results

The Pareto optimal solutions for the bi-objective optimization formulations previously presented were obtained through an extensive search for both illustrative examples. The optimal adaptation strategies determined for the pessimistic formulation, optimistic formulation, and the robust formulation are shown in Fig. 6a, b, and c, respectively, for Example A. The top plots shows the tradeoff between the two objectives in the Pareto optimal solution set. The marker type denotes the specific adaptation action that is implemented. Since timing is also a design variable in the optimization routine, the bottom plots are included. They are 3-dimensional representations of the Pareto optimal solutions where the timing of the adaptation action is on the vertical axis. These set of plots enable the shape of the Pareto front to be noted, and the timing and type of adaptation to be presented concisely.In the pessimistic formulation (i.e. $\max_{\Phi}(\min_{\Psi} BCR_{mk})$ and $\max_{\Phi}(\min_{\Psi} GLR_{mk})$), the worst-case scenario is being planned for. In order to maximize the minimum BCR for Example A, the application of shear keys is performed at $t_a^* = 0$ (denoted as A1 in Fig. 6a). Economic efficiency is maximized when the structure is adapted as soon as possible. However, there is no flexibility (i.e. GLR = 0) in this solution. The maximum flexibility (i.e. largest GLR) is achieved when riprap and restrainers are applied at year 1 (denoted as A2 in Fig. 6a). This may appear contradictory to the desire for flexibility in an adaptation strategy. However, it stems from the maximin formulation: by maximizing the minimums, only the worst climate change scenario is being addressed. If the worst-case scenario suggests any intensification of the hazard, the pessimistic model negates any desire for flexibility. Thus, for Example A, the pessimistic formulation fundamentally negates any desire for flexibility. However, it is useful since it does not require an estimation of the probability of different climate scenarios.The Pareto optimal solutions for the optimistic formulation (i.e. $\max_{\Phi}(\max_{\Psi} BCR_{mk})$ and $\max_{\Phi}(\max_{\Psi} GLR_{mk})$) are shown in Fig. 6b. The two separate groupings

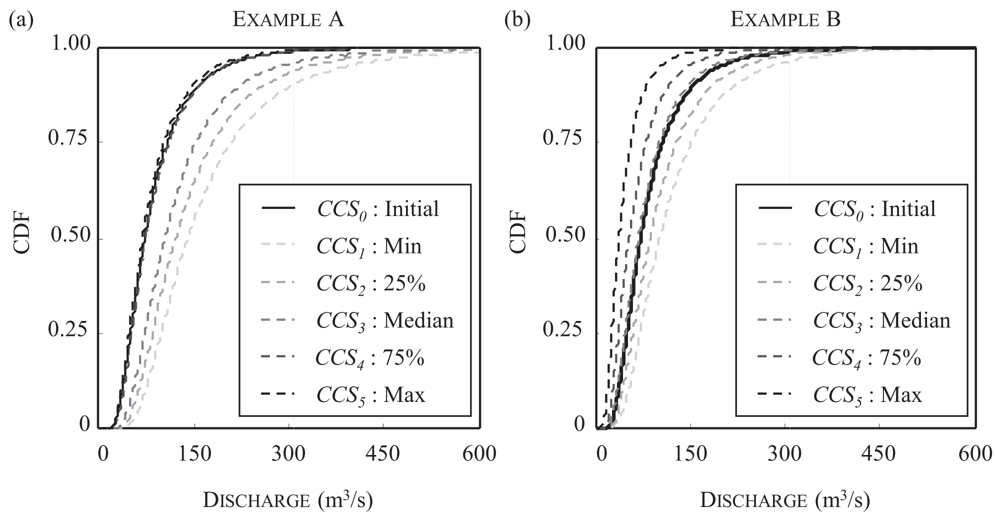

Fig. 4. Discharge distribution for the current climate (solid black line) and the future climate (dashed lines) for the climate change scenarios included for (a) Example A, and (b) Example B.

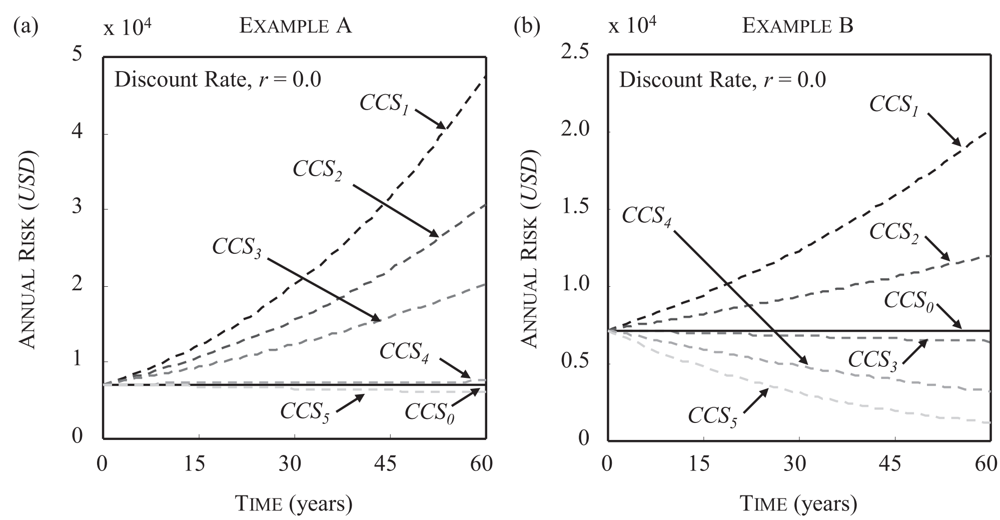

Fig. 5. Time-variant risk profiles for the example bridge under a stationary (current) climate (solid black line) and the future climate (dashed lines) for the climate change scenarios included for (a) Example A, and (b) Example B.

include (1) adaptation strategies with 2 retrofit measures are applied (denoted as Set 1 in Fig. 6b), and (2) adaptation strategies with only 1 retrofit measure is applied (denoted as Set 2 in Fig. 6b). This is due to the manner in which gains are defined; allowing for a larger magnitude in the gains for the adaptation strategies with 2 retrofit measures. Additionally, among the separate groupings, solutions with the largest GLR are applied later in the planning horizon. The adaptation strategy with the highest gain-loss ratio includes the application of riprap and shear keys at year 59. This is the year just before the planning horizon is reached, the latest t_a considered in Φ. For locations where there is at least one potential scenario where the flooding intensity may decrease, and an optimistic outlook on future scenarios considered (as is the case with the optimistic formulation) the gains that can be accrued by waiting for more information are high, and losses low. The trade-off between the GLR and BCR as seen in Fig. 6b reinforces the concept that efficiency and flexibility are two competing metrics.

However, the bi-objective optimistic formulation dictates the assumption that the future scenarios that are optimal for both efficiency (i.e. BCR) and flexibility (i.e. GLR) are realized. However, since these are conflicting objectives, the climate scenario that maximizes the BCR for adaptation strategy m is not always the same as the climate scenario that maximizes the GLR. For instance, the Pareto optimal solution B1, as indicated in Fig. 6b, includes the application of riprap and restrainers at year 31. Fig. 7 details the BCR and GLR of this management strategy (i.e. applying riprap and restrainers at year 31) for climate change scenarios 1 through 5, as well as the BCR-GLR pair that is included in the optimistic, pessimistic and robust solution. It is apparent that the realization of climate change scenario CCS_5 corresponds with the maximum GLR, while the realization of CCS_1 corresponds with the maximum BCR. By maximizing the maximums of both metrics, the solution to the optimistic formulation corresponds to a point that is unrealistic under any future scenario. Conversely, by maximizing the minimum of both metrics, the optimal solution corresponds to a conservative estimate of BCR and GLR and will be outperformed under a realization of any future scenario.

The robust formulation, which maximizes the robustness index of each metric, accounts for the variability amongst the different scenarios rather than just the worst or best case. The most flexible solutions (i.e. solutions with the largest GLR) for the robust formulation also indicate that adaptation should occur early in the planning horizon for example A. This is attributed to the intensification of the hazard expected in CCS_1, CCS_2, CCS_3, and CCS_4. The low gain-loss ratios associated with delayed adaptation under these scenarios outweigh the higher GLR expected if CCS_5 is realized. Since the robustness metric considers how

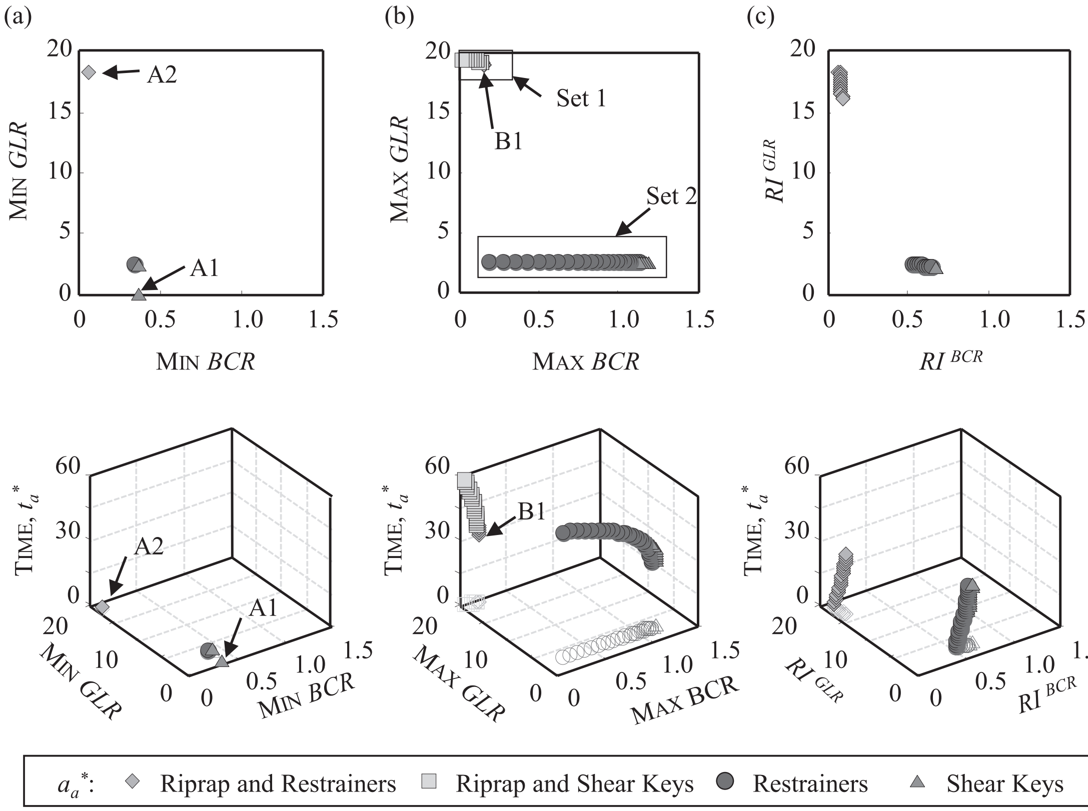

Fig. 6. Pareto optimal solutions for the (a) pessimistic formulation, (b) optimistic formulation, and (c) robust formulation considering climate changes in River A. The top plots include the 2D presentation of the Pareto optimal solutions, and the bottom plots show the Pareto optimal solutions 3D and also include the projection onto the 2D surface.

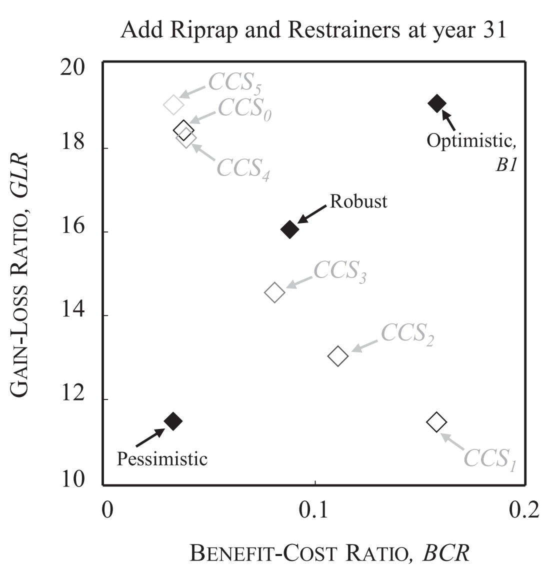

Fig. 7. The BCR and GLR of the management strategy where riprap and restrainers are applied at year 31 for the climate change scenarios predicted for River A.

an adaptation strategy performs across all scenarios (Eq. (12)), the early adaptation yields the largest robustness in flexibility RI^{GLR} for Example A. Thus, the desire to delay adaptation (i.e. an inherent desire to be flexible and wait for more information before acting) is not beneficial. This conclusion, however, is site specific.

The comparison of the Pareto optimal solutions for Example A and Example B provides insight into the importance of the spatial variation of the climate change effects. In Fig. 8a, b, and c, the Pareto optimal solutions for the pessimistic formulation, optimistic formulation, and the robust formulation are illustrated, respectively, for Example B. Similar to Example A, the optimal solutions for Example B for the pessimistic formulation yield adaptation strategies that require immediate action (i.e. at year 0 or year 1). This, again, is due to the assumption that the worst-case scenario will be realized. The worst-case scenario for Example B also includes an intensification of the flooding hazard. The Pareto optimal solutions for the optimistic approach for Example B demonstrate the same trade-off between objectives and include options that range in application time. The options that have the highest flexibility (i.e. GLR) are applied later in life, while the most economically efficient option is applied at year 23. The assumed interest rate, $r = 0.04$, and the relatively large decrease in the intensity of the hazard in the best-case scenario for River B leads to the most economically beneficial strategy that includes a delay in adaptation actions.

The optimal adaptation strategies found for the example bridge over River B for the robust model highlights the validity of the desire for flexible solutions. In Example B, the financial gains associated with delaying adaptation outweigh the losses that may accrue. The most flexible strategy delays the application of adaptation actions. While this solution is the most flexible, there is no benefit associated with it. Thus, the group of decision makers must decide on the preference that will be given to BCR and GLR when determining a course of action. Additionally, the optimal strategies identified for Examples A and B for the robust formulation of the climate change adaptation problem shows that the desire for flexibility may be systematically justified for a certain site. However, for other sites, the "wait and see" mentality cannot be systematically justified when valuing the potential gains and losses associated with delay.

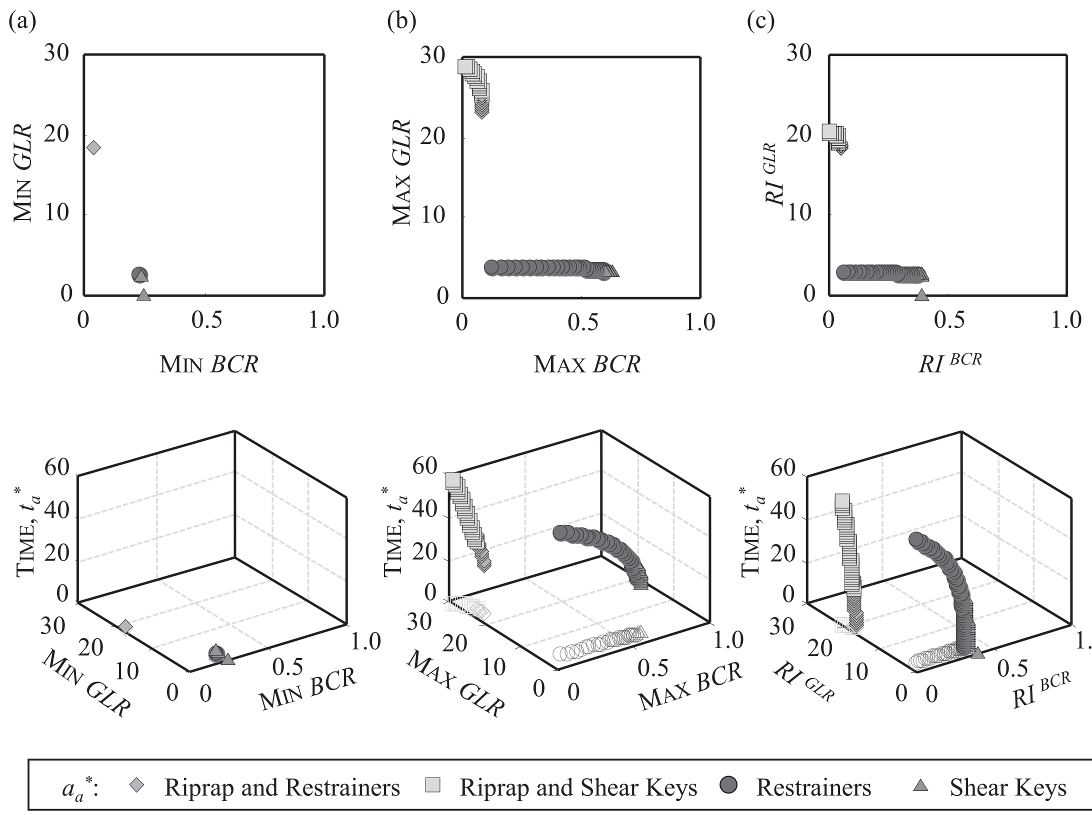

Fig. 8. Pareto optimal solutions for the (a) pessimistic formulation, (b) optimistic formulation, and (c) robust formulation considering climate changes in River B. The top plots include the 2D presentation of the Pareto optimal solutions, and the bottom plots show the Pareto optimal solutions 3D and also include the projection onto the 2D surface.

9. Conclusions

Robust optimization models aid in the decision-making process for adapting civil infrastructure to a changing climate. The deep uncertainties associated with future climate scenarios that stem from both the variety of GCMs that may be used to predict future climate and the different RCPs which define potential future Greenhouse Gas concentrations must be systematically integrated into the decision making process. This paper outlines the application of robust optimization formulations for identifying optimal climate change adaptation strategies in order to address quantifiable and deep uncertainties. Bi-objective formulations aid in identifying strategies that are both flexible and beneficial. Additionally, this paper proposes a clear and systematic methodology to quantify the desire for flexibility through the use of the gain-loss ratio. The optimization models are applied to two illustrative examples that consider a typical bridge over two rivers having comparable climate change trends to the (A) Columbia River and (B) Mississippi River. In the former, flooding is consistently anticipated to intensify, while in the later, flooding is consistently expected to become less intense. The optimal management strategies for the three robust optimization models were developed for the illustrative Examples A and B. The following conclusions are drawn:

1. The pessimistic formulation yields solutions that plan for the worst-case scenario. As such, there are no potential gains by delaying adaptation if the worst-case scenario includes an intensification of the hazard. This conservative formulation is useful for risk averse decision markers, but antithetical to the desire for flexibility.
2. The bi-objective optimistic formulation is useful for decision makers who do not want to assign any probability of occurrence to climate scenarios. However, the Pareto front represents unattainable value, since the maximum values for BCR and GLR require the realization of different scenarios.
3. The robustness formulation considers the dispersion in the performance of adaptation strategies over all potential scenarios. However, the formulation of the robustness index assigns an equal likelihood to all potential scenarios. It does not differentiate between positive and negative values of the payoff metrics (i.e. BCR or GLR) and thus has a significant drawback to implementation.
4. In regions where the climate change scenarios include an overall intensification of the hazard, the desire for flexibility is outweighed by the need to adapt in order to prevent significant losses.
5. In regions where the climate change scenarios include an overall decrease in the intensity of the hazard, the desire for flexibility can lead to optimal adaptation strategies that delay adaptation until additional information is available. There is a trade-off between the objectives of economic efficiency and flexibility where low BCR must be accepted for high GLR and vice versa.

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